

Forging An Optimized Bayesian Network Model With Selected Parameters For Detection of The Coronavirus In Delta State of Nigeria

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Abstract

Machine learning algorithm have become veritable tools for effective decision support towards the construction of systems that assist experts (individuals) in their field of exploits and endeavor with regards to problematic tasks.. They are best suited for tasks where data is explored and exploited; and cases where the dataset contains noise, partial truth, ambiguities and in cases where there is shortage of datasets. For this study, we employ the Bayesian network to construct a model trained towards a target system that can help predict best parameters used for classification of the novel coronavirus (covid-19). Data was collected from Federal Medical Center Epidemiology laboratory (a centralized databank for all cases of the covid-19 in Delta State). Data was split into training and investigation (test) dataset for the target system. Results show high predictive capability.

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Keywords: Coronavirus, covid-19, Nigeria, machine learning, malware, Bayesian Network, epidemiology, pandemic

1. Introduction

The advent of the coronavirus (Covid-19) has unravelled to the world today, a pandemic whose increased mortality rate is targeted at senior 'aged' citizens, patients with low immunology, patients with chronic diseases, amongst others. The novel coronavirus (COVID-19) caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) emerged in the city of Wuhan, China in late December 2019 and was declared a global pandemic by the World Health Organization (WHO) on 11 March 2020 [1]. In the time since, the disease has quickly spread to all continents and, to date, over 1.6 million cases have been recorded with a fatality rate of 6.19% noted on 11 April 2020 [2].

Thus far, the risk of COVID-19 importation from Europe to Africa is higher than the risk of importation from China [3]. In their study, Martinez-Alvarez et al. [4] compared transmission of COVID-19 (within 6 days after the first cases were detected) in selected countries and observed a more rapid spread of the virus in some West African countries than in Europe [4]. The situation in African countries could be worse than what is being reported, as most of the countries are inadequately prepared for disease outbreak due to poor disease surveillance and response systems as well as inadequate and overstretched health facilities and services. Also, African countries with highest importation

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risk have also been found to possess a high capacity to respond to outbreaks [5]. As of 23 June 2020, Nigeria has a total of 21,317 confirmed cases and 533 deaths from COVID-19 [6].

1.1. Nigeria and The Delta State Frontiers: The Covid-19 Pandemic

The first confirmed case of COVID-19 infection in Nigeria was proclaimed on 27, February, 2020 once the Italian national in urban Lagos tested positive for the virus. Since then, the quantity of confirmed cases of the virus has been increasing daily across the country. The pandemic has spread to all the 36 states of Nigeria and lastly Abuja, the Federal Capital Territory. The immediate reaction of sub-national governments in Nigeria to COVID-19 is that the NCDC implementation campaign for social distancing via closure of facilities and reducing the range of people at totally different gatherings together with places of worships [7]. Many states have restricted airports and inter-state travel. Open markets are closed or allowed to open at specific hours so as for state agencies to clean those areas for COVID-19. Some state governments in Nigeria have adopted additional vital measures such as curfews and laws restricting both intra-state and inter-state migration. However, these law have been found to be a bit flexible and applies less to transportation and movement of procuring essential supplies such as food, water, prescription drugs, medical supplies and medicines; and any other essential supply the Governor might take for necessary use. Many states have stepped up to supply emergency isolation and treatment centers in addition to the various palliatives to the foremost vulnerable persons in their domain [7,8,9].

1.2. Causatives on The Fast-Paced Spread Propagation in Nigeria

The Covid-19 pandemic is quite an unfortunate incidence; But, it has provided opportunity for government and stakeholders to draw lessons from the experience(s), which includes (and not limited to) [7, 10] as below:

1. Late Closure of Borders: Nigeria's air and land borders were closed on March 2020, over 3 weeks once the first recorded patient of Italian nationality was declared. Movement and migration intercity remained unrestricted until April 2020. The delay to shut borders and limit inter-city migration inflated the quantity of foreign cases and is basically liable for the continual increase in community transmission within the nation, spreading into various states. The presidency had to be compelled to be proactive (rather than reactionary) in handling problems with national/international importance.
2. Border Closure to contain COVID-19: The porous nature of Nigeria's land borders makes it troublesome for the country to satisfactorily secure its citizens and stem the tide of the novel coronavirus pandemic by keeping its land borders shut. Nigeria presently contends with the issues of cross-border importing and gun running, in addition to cross-border movement of Fulani herdsmen from alternative West African Countries into its territory. With COVID-19 being transmitted via migration from one country to another, there is concern that the itinerant herders may presently become veritable agent of community transmission. The Nigeria immigration Service must appraise its Border Management Strategy (2019-2023) and change it comprehensively to tackle the rising challenges.
3. Social Protection: Federal government's call to use National Social Register of Poor and Vulnerable Households that has not been updated since 2016 as knowledgebase to distribute N20,000 (Nigerian monetary unit) (\$52) conditional money transfers palliatives to the poor means solely a fraction of Nigerians who need economic help are going to be reached. This drawback is combined by the shortage of potency and effectiveness of the distribution mechanisms to reach households that are worst-hit by the pandemic. Also, the NCDC has extended a public health campaign to inform individuals of the necessity to follow social distancing and to encourage personal hygiene, together with hand laundry with running water, this could be trouble to some to attain in low-income communities and internally displaced person camps, where individuals are gorged in areas with very little or no access to basic wants, together with water. This shows that Nigeria does not presently have a sturdy set up or strategy to deliver social and economic help to the tens of countless folks that would require help because of COVID-19. Government must be compelled to develop additional responses, creativity, and transparency to ensure the essential needs of life to everyone.
4. Fragility of the economy within the face of COVID-19: The Nigeria economy was even before COVID-19 facing head-winds from rising external vulnerabilities and falling per capita GDP levels. There has been a deficiency in income compared to payment that rose from N2.2 trillion to N5.18 trillion. The deficiency is as a result of declining output and falling costs of crude within the international oil market. The pandemic at the side of the sharp fall in oil costs and outputs has increased vulnerabilities in Nigeria's economy, resulting in a historic decrease in growth and enormous scale finance. Borrowing has since become a measure taken by the national

government to satisfy this gap. International Monetary Fund (IMF) has approved a loan of \$3.4billion as Emergency Support Fund additionally to \$2,179,609, 890 (N850billion) packages approved by the parliament. A new \$6.7billion credit is in the offing. Should costs and demand for fossil fuel persist at the present red zone; the capability of Nigeria to contain COVID-19 is going to be greatly hampered. The lesson(s) therein has educated Nigeria therein, is that turning more and more dependence majorly on oil as a supply of funding for the economy has become dangerous. There is need to urgently diversify the economy and cut the value of governance.

1.3. Motivation of The Study

In Nigeria (and Delta State), a number of its population is known to suffer from infectious diseases such as malaria, Lassa fever, flaccid paralysis, cerebrospinal meningitis etc. These conditions, additionally worsened by lack of well-equipped medical infrastructure and insufficient medical care – potentially increases the potential spread and patients' mortality rate from covid-19. Treatment for afflicted patients is often via use of antibiotic (prescriptions for malaria) to subdue the virus' spread. This method (though remains adopted) has its problems due: (a) the short course of antibiotics used (though remains the adopted mode) for treating infected patients, which takes fourteen days of isolation, is needed to maximally subdue the virus within the afflicted body, and (b) the ever-changing frontiers views of the World Health Organization and other stakeholders from what drugs to administer (asides the social distancing campaign, hygiene precautions etc). To efficiently tackle this malicious disease seem to have become a continuous and soon 'inconclusive' task as many studies are hampered in performance both the views mentioned above.

To overcome shortfalls in the adoption of machine learning schemes to handle malicious data, we employ the Bayesian network to help with feature and parameter selection that will aid the reduced spread and propagation of the covid-19 disease with enhanced detection and accurate classification. Thus, study seeks to aid medical practitioners with a decision support inference information from a database that will help to predict potential spread and propagation symptoms from earlier cases that can possibly match some criteria such as defaulting, while using their limited resources wisely and effectively.

2. Materials And Methods

2.1. Dataset Gathering

There are over eight isolation centers per senatorial district as created by the Delta State Government in response to curb the spread of the covid-19 pandemic. Figure 1 shows the map of Nigeria's affected states. However, for February 27 to June 23, NCDC daily epidemic curve in Nigeria is shown in figure 2; while, the known reported cases of the pandemic in Delta State is given by table 1. With the consequent spread of the Coronavirus (covid-19) in Nigeria alongside the migration of patients and individuals within and outside of the various states within the nation and abroad, it called on the urgency by the Federal Government of Nigeria to declare travel cum migration bans both intra-states, inter-states and outside of the Nigeria state.

No	Description of Cases	Population
1	Total Samples Tested	1868
	Previously Confirmed Cases	569
	Newly Confirmed Case(s)	37
2	Previously Discharged Cases	136
	Newly Discharged Cases	6
3	Total Deaths	20
4	Total Active Cases	413
5	Total Number of Patients Abscond	0
6	Days since last reported case	0

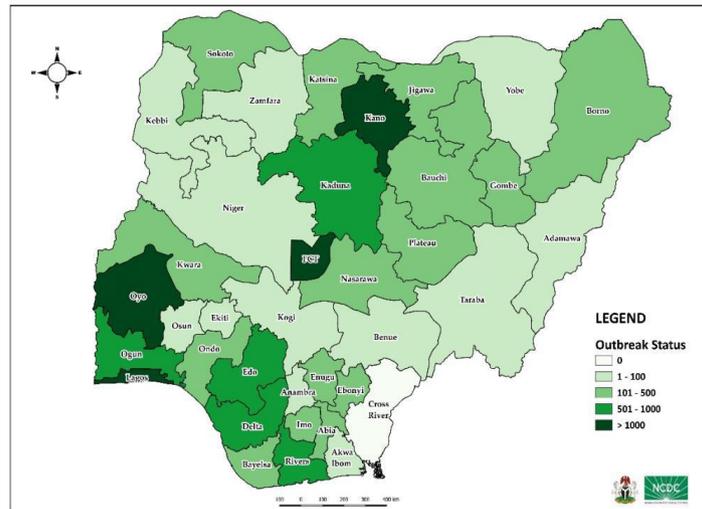


Figure 1. Map of Nigeria showing affected States

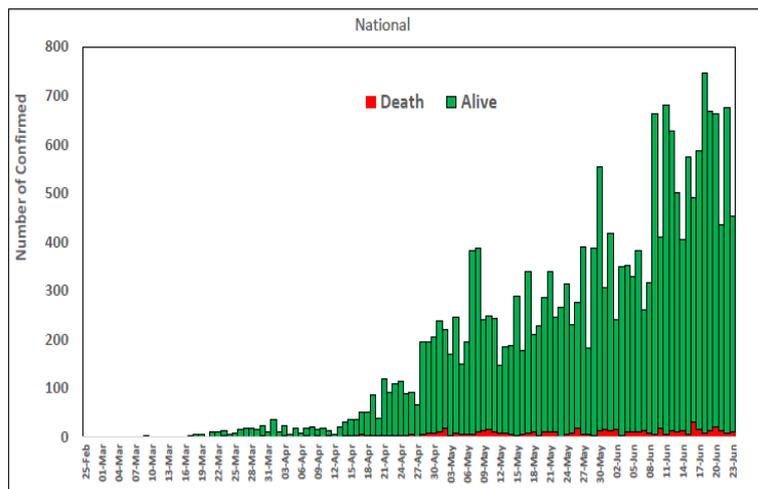


Figure 2. Confirmed cases (Feb 27 – Jun 23, 2020)

2.2. Data Preparation and Verification

Machine learning model/algorithm often requires gathering of the necessary dataset as cases, examples, and instances of all possible object classes. This is because in order to effectively train the adopted and adapted model, instances of the dataset must be appropriately labeled in order to minimize the error rate in the classification. These errors discern cum determine how effective and efficient the model progressed and is able to mine the data features of interest. Also, these errors can be resultant of the fact that in grouping cum labeling the data, some data points – even when not in the same class or group, can have lots of similarities under the unsupervised learning, or as they are used to predict new objects in a class under supervised learning. Also, the dataset must also be formatted appropriately to be used by the model; Else, it will result in data-type mismatch as the users tries to encode the data (via pre-processing stages) so that model is adequately trained to classify the data points into their corresponding classes.

For this study, we retrieved the data from the Federal Medical Centre Epidemiology laboratory (Epi-lab) in Asaba, Delta State in Nigeria. The dataset contains about 54 attributes and 4,687 instances, including personal data of the patient, symptoms the patient suffers from, HIV and other tests, history of the disease, diagnostic tools used, treatment that includes regimens for the type of the disease and doses given, with its drug reaction, the follow-up

results for the whole treatment period, also costs and hospitalization paid. However, attributes that are likely to affect the patient behavior towards the treatment (treatment outcome is one of the following: cured, treatment completed, treatment failed, treatment discontinued, death, and transferred out). The dataset was further categorized into:

1. Attributes related to particular patient (age, sex, etc)
2. Attributes that are related to regimen
3. Attributes that are related to proximity to health center
4. Attribute related to treatment's side effect (social or clinical)
5. Attributes that are related to duration of treatment

Here, BN is applied to the pre-processed dataset and the study notes there are some interesting statistics about the attributes concerning the class distribution over the values of each attribute, (b) results of BN model is presented and discussed. There are five steps in this work explained via Figure 1 namely: (a) data gathering, (b) data pre-processing ensures the rightly formatted dataset is used and selection of features of interest, (c) data analysis process involves knowing which operations to encode into the model, data attribute's selections, data type transformation from one type to another type such as a number to be nominal, process the missed data etc, (d) data-mining, which involves learning of the relationship between the overall attributes and probability of the underlying features of interest with target algorithm deployed and implemented in order to construct the prediction model, and (e) evaluate our model by domain expert, comparing the results with other researchers, or by sensitivity analysis. If the model achieves the acceptable accuracy then the process will terminate otherwise the third step will be repeated.

2.3. Limitations of The Study

The following were observed as limitations of the study:

1. Data Preparation – At the data gathering stage, source data is usually collected to contain therein feats that may not be required by the researcher or modeler. These unwanted data feats are stripped from the source data at pre-processing in readiness for implementation of the model and formulation of the target prediction model, often result in the non-fitness of the model (even though from the data feats of interest chosen by most modelers, their algorithms have been tuned to be adapted to the chosen model design).
2. These data transformations often introduce some conflicts in the dataset used such as ambiguities, noise and partial knowledge during labeling for supervised learning.
3. It has also be noted that selection of parameter of interest has its impact on model performance and can often result from over-fitting and over-training of the trained model in readiness for the formulation of the target prediction model.

2.4. Experimental Bayesian Network Model

The Bayesian network (BN) is a directed acyclic graph that is commonly used in many domains which includes software reliability assessment and prediction [11,12], medical diagnosis [13,14]. Based on Bayes theorem of conditional probabilities of random events, BN is a probabilistic model that uses a directed cycle graph to represent the random variables by nodes, which are connected by edges. The edge connect nodes A to B, where A as a parent node, represents a conditional probability $P(B, A)$ [15, 16]. Selection of algorithms depends on various factors, which includes availability of data (as an important feature that impacts on an algorithm's performance). A crucial feat of BN is its tolerance for noisy, incomplete data [9] as it seeks to achieve good performance when the attribute is large.

BN has been successfully applied to medicine, machine learning, signal processing etc. BN represents knowledge and exploits data via a mathematical structure with simplified visual representations of graphic probability relations between a set of variables under domain of uncertainty [17]. BN is structured as a directed graph and conditional probability tables (CPTs) given the occurrence of its parent nodes. BN probability is related to the degree of belief – measuring plausibility of an event given incomplete knowledge. It states the probability of an event A conditional on another event B denoted as $P(A|B)$; And it is generally different from probability of B conditional on A written as $P(B|A)$. It implies that: (a) there is a definite relation between events $P(A|B)$ and $P(B|A)$, and Bayes theorem is the statement of such relations, (b) it computes $P(A|B)$ given the data about $P(B|A)$, and lastly, (c) its result employs new data to update the conditional probability of an event [18-20].

Given a sample space s , with a set of mutually exclusive events (A_1, A_2, \dots, A_n) from $s - B$ is any event from s whose probability is denoted as $P(B) > 0$. Using Bayes theorem, BN is described via Equation 1 and 2 [21-24]:

$$P(A_k|B) = \frac{P(A_k \cap B)}{P(A_1 \cap B) + P(A_2 \cap B) + \dots + P(A_n \cap B)} \quad (1)$$

Invoking: $P(A_k|B) = P(A_k).P(B|A_k)$ – probability becomes:

$$P(A_k|B) = \frac{P(A_k).P(B|A_k)}{P(A_1).P(B|A_1) + P(A_2).P(B|A_2) + \dots + P(A_n).P(B|A_n)} \quad (2)$$

For the BN classifier, we built the model to train the dataset via a conditional probability table (CPT) so that the algorithm first seeks to learn the structure of the BN. After which, it learns the training dataset labels (cum data points based on parameter(s) or feats of interest). It then builds the probability distribution tables for each nodal relationship in the network. It achieves this via two learning processes namely: (a) structured learning or casual discovery in which the Bayesian network learns the structure and parameters provided with the input dataset. The causal discovery is learned via using either of K_2 , Hill climbing and Tabu-Search, and (b) it achieves probability distribution learning with algorithms like BN estimator and multinomial estimator. Once, structure is learned and parameter(s) learning is completed for CPT for each feat in the BN, investigation cum testing of the model can commence [25-29].

To apply BN for detection of the novel corona virus (covid-19) treatment, we adopt selected parameters whose probability distribution will yield the appropriate stochastic outcomes for the underlying feats of interest. To classify the data-points, we use the supervised learning model for the Bayesian network designed as in figure 3 below:

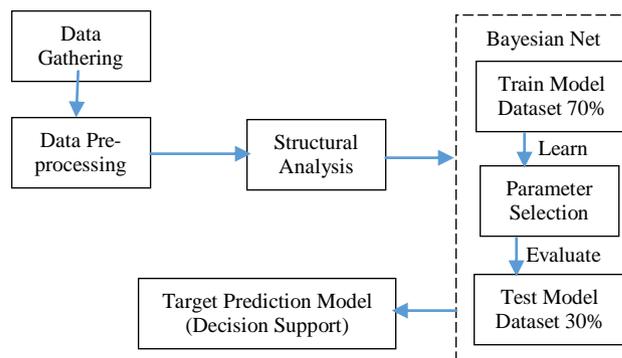


Figure 3. Target Prediction Model Construction

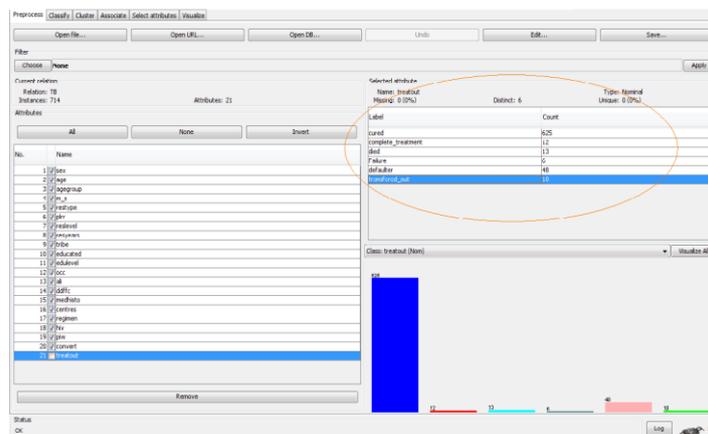


Figure 4. Data Loading unto the Target Prediction Model

3. Findings and Discussion(s)

The application of Bayesian model with 5-fold retraining and/or cross validation in evaluating the prediction model based on the correctly classified instances, the model has produced 93.7563 percent accuracy rate (see Table 2)

showing confusion matrix with the five classes (a,b,c,d,e) representing the various treatment outcome groups. A confusion matrix represents per true and false classes correct classification. Table 2 shows that confirmed class of 568 cases. Then the discharged class of 134 cases correctly classified as *true* as in class (a); while, 2 others (from b-to-e) classified as false. Classes (a) and (b) respectively shows no significant difference between them. Thus, the error in the classification do not have significant effect. But, the general percentage obtained from software (correctly classified instances) for proposed Bayesian model is 93.7563 percent.

Figure 5 below describes that for the study, the root nodes represents treatment outcome attributes and independent leaves represents other attributes. Some of the assumption(s) made here includes that: (a) the variables are statistically independent, and (b) all variables are completely independent in accordance with [21-23] – though, it is observed that the independent assumption can barely arise [29].

Table 2. Confusion Matrix and Percentage Achieved by Model

Class	a	b	c	d	e
a=Confirmed	568	1	0	0	0
b=Discharged	134	0	1	0	1
c=Death	20	0	3	5	0
d=Active	409	0	2	1	2
e=Absconded	2	0	0	1	0

There is a relation between variables shown in Table 3, which represent the probabilities of the variable. Note that discharge class is dependent upon variable (piw) by 0.962 probabilities. Thus, we can violate the independent assumption “no more than one parent”. This is expressed by the set (maxNrOfParents=1) with which this process leads to achieve 94-percent accuracy. And the graphical model changes as in Figure 5 that describes how the probability distribution effect on model representation. We notice the relations between attributes and their affection to the prediction result in accordance with [28, 29].

Table 3. Probability Distribution of (piw) Variable

Class	Yes	No
a=Confirmed	0.999	0.001
b=Discharged	0.962	0.038
c=Death	0.107	0.893
d=Active	0.01	0.99
e=Absconded	0.136	0.864

4. Summary, Recommendation and Conclusions

In the study, we employed the Bayesian Network as proposed predictive techniques to construct a target model for predicting potential spread and classification of the coronavirus (covid-19) disease. Moreover, this study used medical dataset gathered from the Federal Medical Center Epidemiology laboratory at Asaba in Delta State. The Bayesian Network model produced acceptable accuracy and better performance via the violation of the independent assumptions. This violation was based on the probability distribution of attributes. The proposed model, if prospectively confirmed, will be useful in guiding medical and health practitioners in estimating the risk of smear-positive covid-19 case treatment. The model will serve as useful and cost-effective tool in a health care system wherein there exist limited resources. Furthermore, the Bayesian Network can be used as best predictive tools for constructing prediction models to solve problems on other domains (to include and not limited to) reliability prediction of component based systems. There are various machine learning techniques that were not examined here (due to time constraints) – they may also be effective in dealing with such uncertainty and classification task such as Rule Induction, Support Vector Machine, Principal Component Analysis, and others. Finally, the authors of this study believed that the machine learning techniques used in this paper warrant further investigation, particularly to explore the conditions and attributes under which this study was carried out as well as seek other conditions, in this underlined problem where they are most likely to be effective.

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